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How Does Algorithm Control Affect Platform Workers' Responses? Algorithm as a Digital Taylorism

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Abstract: While many online labor platforms have adopted algorithms to monitor or control workforces as a new form of algorithm management, there is no academic attempt to empirically examine how the algorithmic control of platforms influences platform workers' behaviors in a platform context. In this study, we consider how algorithm management affects the platform workers' response from a Digital Taylorism perspective. Digital Taylorism involves management's use of technology to monitor workers by assigning and tracking work. Therefore, this study examines how algorithm control influences the platform workers' response by mediating the tension of work compensation in an online labor platform context. Survey data collected from 216 food delivery riders in South Korea are used to test the model using partial least squares analysis. Our results show that algorithm control affects platform workers' responses by mediating tensions of platform work compensation. Based upon our empirical findings, we can provide a theoretical perspective to relevant researchers who seek to find a theoretical mechanism of algorithm management. Moreover, we can offer practical insights to practitioners who are interested in algorithm management.

Keywords: algorithm control; uncertainty; repeatability; embracing; switching

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1. Introduction

Algorithms are at the core of almost every company in the digital platform economy. For example, Uber, a well-known platform company, uses an algorithm to match the demand (customer) and supply (driver), and also control the drivers' behavior. Through this, Uber influences consumers' decisions and the drivers' work practices. Like Uber, many online labor platforms also adopt algorithms to monitor and control the platform workforce and optimize the efficiency of matching processes [1,2]. Relevant research has termed this new form, algorithm management [1,3,4]. Möhlmann et al. [2] refers to algorithm management as the, "large-scale collection and use of data on a platform to develop and improve learning algorithms that carry out coordination and control functions traditionally performed by managers" (p. 2001). The algorithm management can 'match' consumers with platform workers and seek to 'control' their behavior [2].

While algorithm management can generate some benefits for platform companies, prior work suggests it could cause work environment tensions that may result in frustration or confusion among platform workers [1,3,5,6]. On the other hand, platform workers tend to think of the algorithms as highly opaque "black boxes" that interrupt their understanding of the inner workings [1,3,7–9]. For example, algorithmic opacity may cause Uber drivers to experience uncertainties in reward compensations and ride assignments [2]. This phenomenon resides in the same context as the ideas of Taylorism (scientific management) in the past. The primary purpose of Taylorism is that a human manager should systematically monitor the workforce to detect timewasting and direct efforts toward the pursuit of efficiency. Recently, instead of human managers, an algorithm could manage a platform worker's behavior and movement. Digital Taylorism involves management's use of technology to monitor workers and it can be found in many organizations. One example is online labor platforms, because the algorithm monitors and controls the workers' behavior in assigning and tracking their delivery work. This study considers that algorithm management affects the platform workers' response from a Digital Taylorism perspective. Furthermore, while previous studies have found meaningful knowledge for contributing to platform work, there is no attempt to examine the relationship between algorithmic activities and platform workers' behaviors. Therefore, this study examines how algorithm control influences the platform workers' response by mediating the tension of work compensation in an online labor platform context. In order to address this gap, this study attempts to address the following research questions:

How does an algorithm affect platform workers' responses via tensions of platform work compensation, and what role does the tension of work compensation play in the platform environment?

By addressing the above research questions, this study can contribute to a body of knowledge on platform work by examining the relationship between algorithm control and platform workers' responses. In testing our model, we found that the relationships between algorithm control and embracing/switching were mediated by both uncertainty and repeatability of the work assigned by platforms.

Based upon our findings, we contribute to the extant literature in a number of ways. From a theory perspective, this paper offers insights into the link between platform work tensions and platform workers' responses by focusing on the knowledge of algorithmic control. Practically, our findings contribute to the ongoing debate on how platform workers are affected by algorithms. Based on these findings, this study provides platform companies with insights on how to manage platform workers based on their performance.

The remainder of the paper is organized as follows. The next section provides a literature review on Digital Taylorism and some of the research that has been done in this area, particularly focusing on studies that relate to algorithm and platform work. Then, we introduce our research model and hypotheses, followed by the data analysis and results of our study. The implications of our findings are then discussed.

2. Literature Review

In this section, we first present the previous literature relevant to Digital Taylorism and explain why it is related to algorithm management of platforms. Next, we describe algorithm control and platform work, as well as platform workers' reactions to algorithmic management by platforms.

2.1. Digital Taylorism

Digital Taylorism is a theoretical view of the new form of Taylorism resulting from innovation adopted in the organization of work by digital technologies [10–12]. It is a modern take on the management style known as Taylorism (or scientific management). Digital Taylorism focuses on the digitalized nature of work in which digital technologies decompose, measure, and optimize work with the aim of maximizing efficiency [11].

For Digital Taylorism, previous work attempts to present neo-Taylorist scenarios which indicate the transformation of low-skilled work by digital technologies [10,13], explains how work is organized by digital technologies [12], or applies it to describe orchestration of digital platform ecosystems [14]. For instance, Spencer [13] suggests that Digital Taylorism highlighted the potential of new digital technologies to facilitate automation of work or tighten performance measure and control. Most relevant studies draw on Digital Taylorism to explain labor processes in organizations through digital technologies. Digital Taylorism is already becoming entrenched into labor processes in many organizations. Especially for labor in the digital age, the characteristics of Taylorism (including workplace surveillance, control, and deskilling) can be used as a part of an emerging Digital Taylorism [15]. The characteristics of Digital Taylorism can be seen in online digital labor platforms or labor markets under the gig economy [10,16–18].

Among prior work, one notable example of Digital Taylorism is online labor platforms that utilize algorithms, such as Uber. Uber uses Digital Taylorism to perform everyday tasks and monitor drivers. Uber believes this is the most efficient and productive approach [2]. Thus, the jobs of Uber drivers must be organized automatically by the algorithmic architecture of the platform. In addition, it is similar to food delivery platforms, which have rating systems for their platform workers. They will decide automatically or let the users decide whether a task is performed successfully and rate the platform workers accordingly. This system causes embarrassing situations in which platform workers are worried about they are not given work in the future. For them, work rejection means a potential loss of payment, but also potentially restricted access to subsequent work.

Meanwhile, most online labor platforms have algorithm-based technologies for the measurement and surveillance of platform work [2,19]. The algorithms allow the division of labor and a controlled work arrangement. They are precisely standardizing tasks by the means of algorithmic management, and monitoring them in order to organize the work process as well as the automated measuring of results and feedback, which are key characteristics of Digital Taylorism.

While prior work focuses on examining the effects of algorithm management on workers [5,20,21], there is no consideration of algorithm control from the perspective of Digital Taylorism to describe platform workers' reactions. Algorithm control can be seen as Digital Taylorism because the work was assigned, managed, and controlled by the algorithm instruction. This can be understood as Digital Taylorism, which has similarities to the existing Taylorism, such as a dehumanizing effect [12]. Therefore, this study regards the algorithm control in online labor platforms as part of Digital Taylorism and examines how it affects platform workers' responses via tensions of platform work compensation.

2.2. Algorithms and Platform Work

In general, platforms use market mechanisms to match platform labor supply with consumer demand, producing frameworks within which workers can strategize to maximize earnings. Under this condition, they do so within the context of algorithm management that shapes and constrains the platform workers' choices. Platforms also provide application-based marketplaces where consumers and service providers can transact in perfect algorithmic harmony. On the surface, the interests of all stakeholders, including consumers, service providers, and platform workers, are aligned. In particular, due to the algorithm, the more transactions occur, the more customers' needs are met, the more platform workers earn, and the more platform companies collect in revenue. Nevertheless, algorithms could constrain the freedoms of platform workers over work schedules and activities.

The recent literature has recognized that platform companies do not merely match consumers with service providers, but also seek to control the behavior of platform workers [2]. Some researchers have called it 'algorithmic management' [22]. Platforms try to manage and monitor most activities of platform workers using surveillance through customer ratings, performance measures, or behavioral nudges. For example, Möhlmann et al. [2] reported that Uber drivers experienced tensions related to work execution, compensation, and belonging due to the algorithmic control of the Uber platforms.

This study attempts to analyze how platform algorithm control affects workers' responses in a food delivery platform context. While food delivery platforms use algorithmic management to assign delivery work for each platform worker [22], there has been no attempt to examine the relationship between platform algorithm control and platform workers' behavior in this context. Moreover, although the algorithms enable platform workers to work remotely and be flexible in their work schedules [5], they can gradually control platform workers [2,23]. Emerging research on the control of platform work by algorithms is still in its infancy. Therefore, this study illustrates how platform workers are constrained by algorithmic control and its impact on workers' behavioral responses. In particular, this study explores the relationship between algorithm control and platform workers' responses by mediating tensions of platform work in digital online delivery platforms.

2.3. Tensions of Platform Work Compensation

Online labor platforms increasingly adopt algorithmic management to capture large amounts of data about their workforce in real time [1,3,4,23,24]. Requiring vast amounts of data, the algorithms identify patterns and help meaningful decision-making through classifications and predictions [2,25,26].

Although the algorithms are beneficial for online labor platforms, workers under algorithmic management still experience tension in their work surroundings [1–3,6]. For example, despite having a high level of job autonomy or schedule flexibility [5], platform workers still feel controlled by real-time surveillance. Sometimes, they could be penalized and even temporarily banned from platforms for rejecting a job request from the platform [2]. Moreover, prior work has illustrated that platform workers may be victims of discrimination and algorithmic bias [3,27].

Among previous studies, Möhlmann et al. [2] suggest that the tension experienced by the platform workers was associated with their work compensation. They have presented two central work compensation tensions: uncertainty and repeatability. According to Möhlmann et al. [2], platform workers experience uncertainty regarding how much income could be achieved before, during, and after platform work. Platform workers are uncertain how many rides the algorithm would assign them before starting a workday. They are also uncertain if an assigned job would be canceled, increasing their idle time and reducing their income. Furthermore, the platform workers are negatively experiencing traffic and rush hours. If platform workers are stuck in traffic or rush hours on their way, they are uncertain whether the consumer will cancel.

In the case of repeatability, platform workers tend to trust platform algorithms that offer repeated and profitable job opportunities, despite having uncertainty about platform work in general. Unlike existing taxi drivers, Uber drivers do not need to look for passengers on the streets and do not need to advertise and market themselves [2]. When Uber drivers log into the Uber systems, work is almost guaranteed by the algorithm, which finds passengers and matches them with drivers efficiently and effectively. As a result, drivers trust the platform's ability to supply work and earning opportunities on an ongoing basis.

Therefore, this study also considers uncertainty and repeatability as the tension of work compensation. In the present study context (food delivery platforms), food delivery riders can also experience considerable uncertainty about their earnings, but they generally trust that the algorithm will assign repeated and profitable jobs. In particular, this study examines how algorithm control in food delivery platforms influences the food delivery riders' tensions of work compensation, including uncertainty and repeatability, which could lead to workers' responses.

2.4. Platform Workers' Responses

Previous studies have revealed the platform workers' reactions to algorithmic management [2,19,28–31]. Among previous studies, Möhlmann et al. [19] have noted that platform workers who are affected by the tension of work stemming from algorithmic management have two types of behavioral responses, such as organization-like responses and market-like responses.

The organization-like responses refer to platform workers embracing or enjoying their work environment, while the market-like responses refer to platform workers showing opposition to the algorithm's instructions through the articulation of agency [2,29–32].

In this study, we consider two response types as the final dependent variables to understand how the algorithmic control influences food delivery riders' behavior. Algorithmic management is a double-edged sword [19]. Therefore, food delivery riders exposed to the algorithmic management may show organization-like responses (i.e., embracing their loyalty), while they may also show market-like responses (i.e., strategically logging in and out of the app). Thus, this study regards both embracing as an organization-like response and switching as a market-like response for describing the workers' responses to algorithmic management. While previous studies on algorithmic management have meaningful insights, it is unclear how algorithmic management relates to the platform workers' response. It is also empirically unclear how two tensions of work compensation, such as uncertainty and repeatability, influence the workers' responses. Therefore, this study attempts to address these gaps by developing a theoretical research model in which algorithm control leads to workers' responses by mediating work tensions in the food delivery platform context.

3. Research Model and Hypotheses

In this study, we develop a research model of relationships among algorithm control, tensions of platform work compensation, and platform workers' responses. More specifically, this study examines the effect of an algorithm control to platform workers' responses (i.e., embracing and switching) via tensions of work compensation (i.e., uncertainty and repeatability).

3.1. Research Model

Figure 1 presents the research model consisting of five constructs derived from previous research [2,19,28,29,31]. The algorithm control, which serves as a critical predictor in the present model, influences the tensions of platform work compensation leading to workers' responses. In particular, the model posits that the effect of algorithm control on workers' responses is mediated by both uncertainty and repeatability. While this study does not depict the direct path of the algorithm control to workers' responses, such as embracing (EB) and switching (SW), it does examine whether the effects of algorithm control are partially or fully mediated by both uncertainty (UT) and repeatability (RT).

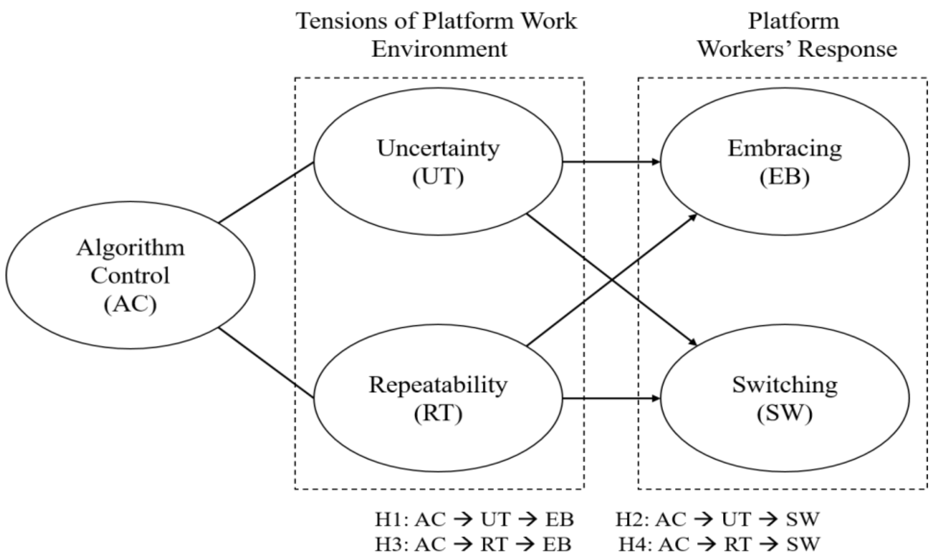

Figure 1. Research Model.

3.2. Research Hypotheses

Prior studies have found that platform workers were uncertain regarding their income and number of rides [2,19]. Platform workers often experience uncertainty about an assigned job by the algorithm. In addition, they are held in traffic and feel uncertain as to whether consumers will cancel. Such uncertainty of work compensation may lead to a platform worker's response.

In line with the above, previous studies have classified platform workers' responses as organization-like and market-like. An example of an organization-like response is embracing, while the market-like response is switching [2,19]. In this study, platform workers' embracing refers to accepting platform algorithms willingly and enthusiastically, while workers' switching refers to moving to alternative platform algorithms during the same work shift. Thus, the uncertainty of work compensation constantly increases as algorithm control is strengthened so that embracing for the platform algorithm can be decreased. In contrast, the switching can be increased by work uncertainty occurring through algorithm control. Based on above argument, therefore, the following hypotheses can be made:

H1. *Algorithm control demotes embracing because it increases uncertainty. Specifically, the relationship between algorithm control and embracing will be mediated by uncertainty.*

H2. *Algorithm control promotes switching because it increases uncertainty. Specifically, the relationship between algorithm control and switching will be mediated by uncertainty.*

According to prior work [2,19], platform workers tend to trust platform algorithms that offer repeated and profitable job opportunities, despite the uncertainty about platform work. In the Uber case, most Uber drivers preferred the algorithm which finds passengers and matches each other efficiently [2,5,33]. Owing to the repeatability, platform workers trust the platforms' ability to supply work endlessly. These platform workers generally reflected their algorithmic interaction, concluding that they were satisfied with their work and showed signs of loyalty [19].

On the other hand, due to repeatability, platform workers often work for more than one platform simultaneously, allowing them to compare the attractiveness of jobs across platforms and to switch back and forth between different systems as they see fit to take advantage of the best earning opportunities. For platform workers, a key motivation for switching is to minimize the idle time and maximize earnings [2]. To do so, they should use multiple smartphones simultaneously, each connected to different platforms. Thus, based on the findings of previous work, repeatability can increase either by embracing or by switching because it minimizes idle time and maximizes earnings. Based on the arguments, the following hypotheses are proposed:

H3. *Algorithm control promotes embracing because it increases repeatability. Specifically, the relationship between algorithm control and embracing will be mediated by repeatability.*

H4. *Algorithm control promotes switching because it increases repeatability. Specifically, the relationship between algorithm control and switching will be mediated by repeatability.*

3.3. Construct Development and Research Approach

This section describes the operationalization of each construct. Multiple measurement items were developed for each construct based on previous studies to improve the reliability of the survey measurement. The actual measurement items are shown in Appendix A. First, based on prior work [2,24], algorithm control was operationalized by capturing the extent to which platform workers feel surveillance, control, and pressure through an algorithm. These form the basis for three of the measurement items (AC1–AC3). Based on Möhlmann et al.'s findings [2], uncertainty and repeatability as the tension of work compensation were developed by creating three measures. Finally, the measures of both embracing and switching were also developed using three items based on Möhlmann et al.'s findings [19]. Since the tension of work compensation and workers' responses cannot be accessed directly, the measurement items were modified based on the findings from previous work [2,31].

For the research approach, platform workers were recruited in the food delivery industry to take a hard-copy-based survey. Food delivery is a rapidly expanding sector of platform work because online grocery and local restaurant delivery sales are constantly increasing [34]. Indeed, South Korean food delivery apps are rushing to offer speedier delivery services by making riders deliver just one order at a time through the algorithm, rather than multiple orders, to ensure the freshness of the food. This is a move borne out of growing competition in the industry. Thus, food delivery workers are considered the main target samples. This study collected survey data from 250 food delivery workers in South

Korea during one month (from January 2022 to February 2022). From an initial sampling frame of 250 workers, 34 responses with mostly missing values from respondents were removed. This left 216 usable responses, with an overall response rate of 86.4%.

4. Data Analysis

In this study, the PLS (partial least squares) technique is adopted to conduct data analysis. This technique has an advantage over traditional statistical methods, including factor analysis, regression analysis, and path analysis, because it can generate a measurement model within the context of the structural model when analyzing small sample size [35]. The PLS technique can perform as effectively as the other statistical techniques (e.g., multiple regression, covariance-based structural equation modeling) in detecting actual paths in terms of accuracy and statistical power under varying conditions of sample size, normality of the data, number of indicators per construct, reliability of the indicators, and complexity of the research model [36]. In particular, it can be utilized to evaluate the efficacy of supplementary analysis in assessing the convergent and discriminant validity of the individual items within the confines of the theoretical model. Under these conditions, the PLS appears to be an appropriate protocol for the testing of our research model; thus, we employed the SmartPLS 3.0 software to evaluate the measurement and structural model [37].

4.1. Sample Demographics

Table 1 lists the demographics of the sample. In the sample, 89.35% of respondents were male, and 50.46% of respondents were married. For platform workers, 92.06% of the respondents had at least one job that includes platform work. The average age of the respondents was 37.9 years (Min = 20, Max = 60).

Table 1. Sample profiles.

Items	Category	Frequency	Ratio (%)
Gender	Male	193	89.35%
	Female	23	10.64%
Marriage	Married	109	50.46%
	Single	100	46.30%
	Celibacy	7	3.24%
Number of Jobs (including platform work)	1	161	74.54%
	2	39	18.06%
	3	13	6.02%
	4	3	1.39%
Age	Mean	37.9	
	Min	20	
	Max	60	
	Median	39	

4.2. Measurement Model

The convergent and discriminant validity are examined for the measurement model [38,39]. First, this study assessed two different approaches for convergent validity, including individual item reliability and construct reliability. For the individual item reliability, it was assessed by examining the item-to-construct loadings for each construct that was measured with multiple indicators.

For the shared variance between each item and its associated construct to exceed the error variance, the standardized loadings should be greater than 0.746. As shown in Appendix B, all item-to-construct loadings exceeded the desired threshold. Second, for the construct reliability, this study calculates Cronbach's alpha, composite reliability, and AVE (average variance extracted) for each block of measures, as shown in Table 2. All the constructs in the measurement model exhibited composite reliabilities of 0.709 or higher. They all exhibited Cronbach's alpha of 0.709 or higher and AVEs of 0.630 or higher.

Table 2. Reliability of Each Construct.

Construct	Mean	Std.	Cronbach's Alpha	Composite Reliability	AVE
Algorithm Control (AC)	5.082	1.341	0.812	0.889	0.727
Embracing (EB)	4.205	1.477	0.763	0.864	0.679
Repeatability (RT)	4.207	1.450	0.745	0.854	0.662
Switching (SW)	4.656	1.560	0.774	0.869	0.688
Uncertainty (UT)	4.960	1.500	0.709	0.835	0.630

All the constructs exceeded the established criteria for AVE. Therefore, all the constructs in this model exceed the threshold judged to be acceptable for construct reliability. Next, discriminant validity is examined after confirming convergent validity. Three tests are conducted for the discriminant validity. First, this study calculates the loading of each indicator on its construct and its cross-loading on all the other constructs, as shown in Appendix B. The loadings of the indicators for each construct are higher than the cross-loadings for the indicators of the other constructs. Furthermore, across the rows, each indicator has a higher loading with its construct than cross-loading with any other construct. In particular, it provides good evidence of discriminant validity [40].

This study also examines whether the AVEs of the constructs are greater than the square of the correlations among the latent constructs, as shown in Appendix C. Reading across the rows of the Tables in Appendix C, the measures passed in this test provide additional evidence of discriminant validity. Lastly, the heterotrait–monotrait ratio of correlations (HTMT) is calculated to assess the discriminant validity. The HTMT criterion measures the average correlations of the indicators across constructs. The acceptable level of discriminant validity (<0.90) was suggested by [41]. The present study provides good evidence of discriminant validity (see Appendix D).

4.3. Testing Hypotheses

Given the sample used in this study, statistical tests can be sensitive and may detect spurious effects [39]. Thus, a strict significance level of 0.001 is accepted for all statistical tests. The explanatory power of a structural model can be evaluated by looking at the R^2 value (variance accounted for) of the final dependent construct. The final dependent constructs in this study (embracing and switching) have R^2 values of 0.430 and 0.110, respectively.

As indicated in Figure 2, the effects of the algorithm control on embracing are fully mediated by uncertainty, while that of algorithm control on switching is not mediated by uncertainty. In addition, the effects of algorithm control on embracing and switching were also fully mediated by repeatability. Our results show strong support for H1, H3, and H4, respectively. H2 was not supported because while algorithm control affects uncertainty, the effect is not passed through the switching. Table 3 lists the results for all of the hypotheses tested.

Table 3. Summary of Testing Hypotheses.

#	Hypothesis	Results
1	Algorithm control demotes embracing because it increases uncertainty. Specifically, the relationship between algorithm control and embracing will be mediated by uncertainty.	Supported
2	Algorithm control promotes switching because it increases uncertainty. Specifically, the relationship between algorithm control and switching will be mediated by uncertainty.	Not supported
3	Algorithm control promotes embracing because it increases repeatability. Specifically, the relationship between algorithm control and embracing will be mediated by repeatability.	Supported
4	Algorithm control promotes switching because it increases repeatability. Specifically, the relationship between algorithm control and switching will be mediated by repeatability	Supported

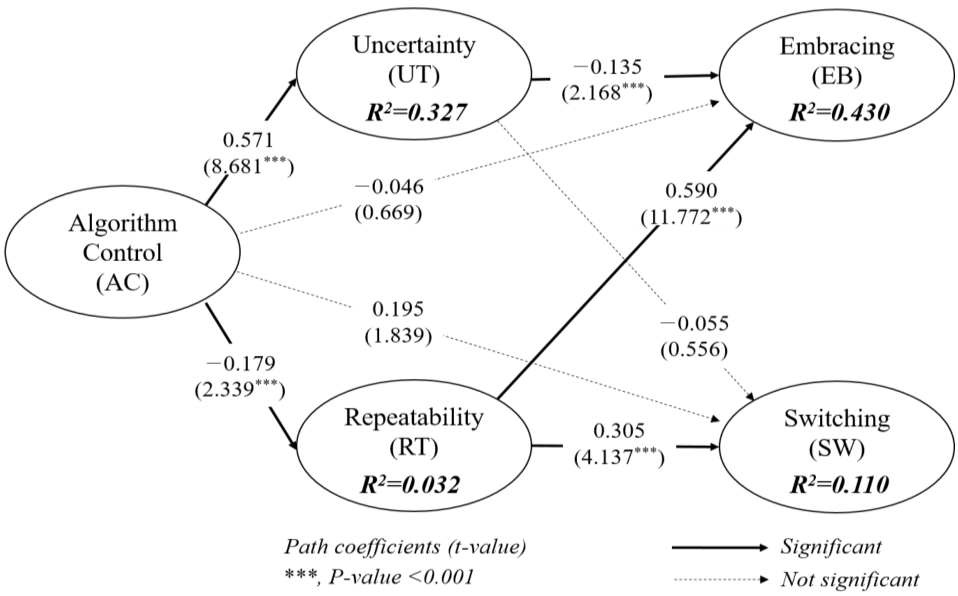

Figure 2. Results of Testing the Hypotheses. *** means p-value < 0.001.

4.4. Discussions

As indicated in Table 3, except for H2, all of the hypotheses were supported. Based on our results, we can discuss the results of testing the hypotheses. First, the path of algorithm control via uncertainty to embracing ($\beta_{(AC \rightarrow UT)}$ = 0.571 and $\beta_{(UT \rightarrow EB)}$ = −0.135) is statistically significant at $p < 0.001$, suggesting that the uncertainty mediates the relationship between algorithm control and embracing (supporting H1). This result supports the arguments in previous work [2]. Based on prior work with our result, we suggest the uncertainty of work compensation could increase when algorithm control was strengthened.

Second, unlike the prediction regarding the relationship between the uncertainty by an algorithm control and platform workers' switching, it is not significant. Based on the findings, there are two interpretations of the result of testing H2. First, in the present case, most respondents worked on the Baemin platform. Thus, the switching for platform workers could be a less dominant issue because there are no dominant competing food delivery platforms in South Korea. (As of 2022, Baemin [www.baemin.com] (accessed on 19 September 2022) accounted for 57.7% of the market, making it by far the leading food delivery platform company. Second place was occupied by Yogiyo [www.yogiyo.co.kr] (accessed on 19 September 2022), with 24.7%, followed in third place by Coupangeat [www.coupangeats.com] (accessed on 19 September 2022), with 17.5% [https://www.hani.

co.kr/arti/economy/consumer/1039479.html] (accessed on 19 September 2022)). Second, in this study, platform workers perceived organization-like behavior (embracing) rather than market-like behavior (switching). Because an algorithm quickly identifies and offers work to one person, the work assigned to each person is considerably faster and more transparent compared to human agencies [2,23]. In general, working arrangements are typically classified as either employment or contract work [23]. While platform work could be a hybrid of contingent work, this indicates that it is closer to employment according to the results of testing H2.

Third, the path of algorithm control via repeatability to embracing ($\beta_{(AC \rightarrow RT)} = -0.179$ and $\beta_{(RT \rightarrow EB)} = 0.590$) is statistically significant at $p < 0.001$, suggesting that the repeatability mediates the relationship between algorithm control and embracing (supporting H3). In our case, while the relationship between AC and RT is negative, the relationship between RT and EB is positively related. In our case, platform workers want repeatability of work assigned by platforms to have profitable job opportunities, while they did not want to be under algorithm control. Our finding was similar to prior work, which platform workers were satisfied and showed signs of loyalty when the platform assigned work repeatedly to them [19].

Lastly, the path of algorithm control via repeatability to switching ($\beta_{(AC \rightarrow RT)} = -0.179$ and $\beta_{(RT \rightarrow sw)} = 0.305$) is statistically significant at $p < 0.001$, suggesting that the repeatability mediates the relationship between algorithm control and switching (supporting H4). Based on previous work [2], our result also shows that repeatability can increase either by embracing or by switching, because it minimizes idle time and maximizes earnings.

In sum, this study explores the effects of algorithm control on platform workers' behavioral responses. Specifically, the effect of the algorithm on embracing and switching is either fully mediated by uncertainty or repeatability as a tension of work compensation. While these findings are based on survey results, they offer interesting insights into the platform workers' responses to algorithm control. The following presents the implications for both research and practice.

5. Conclusions

Although previous studies have contributed to platform work, there is no academic attempt to examine how the algorithmic control of platforms influences platform workers' behaviors from the perspective of Digital Taylorism, which involves management's use of technology to monitor workers. Hence, in this study, we develop and test a research model examining how algorithm control affects platform workers' response through tensions of platform work compensation. We collected 216 survey data from food delivery workers in South Korea. After completing data collection, we analyzed both the measurement model and structural model by PLS technique. Based upon our empirical findings, we provide theoretical insights to relevant researchers who seek to find a theoretical mechanism of algorithm management. We also offer practical insights to practitioners who are interested in algorithm management.

5.1. Research Implications

This study has several implications for research. First, while many online labor platforms adopt algorithms to monitor or control their workforce as new forms of algorithm management, there is no academic attempt to empirically examine how the algorithmic control of platforms influences platform workers' behaviors in a platform context. Moreover, previous studies do not provide statistically valid findings, even though they have suggested the importance of relationships between platform workers' perceptions of the algorithm and workers' behavioral responses [2,30,31,42]. In this study, it is the early research that provides empirical evidence of examining the effects of algorithm control on platform workers' reactions. Specifically, in our study, the effects of algorithm control on platform workers' responses are explored according to the tension of work compensation.

By developing a theoretical model and testing it, this study extends the relevant research on algorithms in platforms by verifying the effects of algorithms on the workers' responses.

Second, compared to previous work, this study provides consistent results regarding the relationship between algorithm control and workers' responses. These results provide empirical evidence that the tensions of work compensation by algorithm control could influence the workers' responses. In particular, both uncertainty and repeatability could play mediating roles in the relationship between algorithm control and the workers' response. Based on these empirical findings, this study could contribute to the studies of researchers who find the salient factors of online labor platforms help explain the behavior of platform workers. In addition, our findings could help researchers who seek a relevant theoretical mechanism for describing platform workers' behavior under algorithm management.

Lastly, this study views algorithm control as Digital Taylorism, which involves management's use of technology to monitor the workers to maximize efficiency in completing each task involved with a given job. The job of food delivery workers is organized mostly automatically by the algorithmic architecture of the platform. This could be a work division that the platform orchestrates automatically and algorithmically. The algorithms are precisely standardizing tasks, algorithmic management, monitoring to organize the work process, and measuring results and feedback, which are the key characteristics of Digital Taylorism. By considering algorithm control as a form of Digital Taylorism, this study offers relevant research and a unique theoretical view to explain the algorithmic management of online labor platforms. We contribute to opening up new avenues for evidence-based discussions about algorithm management from perspective of Digital Taylorism, which allows for new modes of standardization, decomposition, quantification and surveillance of labor by digital technologies.

5.2. Practical Implications

This study has significant implications for practitioners who are interested in platform labor. First, the study explains how algorithms manage platform workers. Specifically, the use of algorithms by the platform to control workers made it more embracing. These results indicate that practitioners of online labor platforms can understand how algorithmic management influences the platform workers' responses. Our findings could provide platform operators with actionable and practical insights on handling algorithm management and thus on how to better balance operating strategies for an effective design of platform-based work.

Second, based on the findings of Möhlmann et al. [2], this study presents two tensions of work compensation, namely uncertainty and repeatability, in order to examine their effects on the workers' responses. According to our results, platform workers have perceived uncertainty about how much money they can expect to make. They also trust the platform's algorithmic matching capabilities to offer them repeated job opportunities. This study suggests possible directions for managers, such as how to manage platform workers' feelings and perceptions. Based on the findings, they could make HRM plans (i.e., the assignment of tasks and performance evaluation) to ensure certain delivery service quality and reliability standards.

Lastly, this study has considered embracing and switching as typical behavioral responses of platform workers. Understanding the two types of responses is important for platform companies to ensure behaviors congruent with the platform's goal and objectives. For many online labor platforms, it is important to know what factors increase platform workers' loyalty to platforms. By considering the workers' responses through algorithms, platform companies could manage platform workers by incentivizing, not sanctioning, so platform workers would choose them over competing platforms. Moreover, considering that low worker retention rates represent a key challenge for online labor platforms, we could offer platform operators insights on how to improve embracing for a platform and reduce switching among platforms based upon our findings.

5.3. Limitations and Future Research

Despite having implications in both research and practical spheres, this study has some limitations. Because of the nature of the survey approach adopted, this study asked the respondents to recall their most recent experiences. Thus, recall bias could be a threat in this setup, because they may not recall their experience accurately. In addition, common method bias (CMB) can be one of the limitations. Thus, a CMB test was conducted to check for any error that could have arisen due to the self-reported survey method. In the present case, a VIF test was conducted using the PLS approach. In this study, all the VIFs in the inner model were lower than 1.562 (see Appendix E). If all VIFs in the inner model resulting from a full collinearity test were equal to or lower than 3.3, the model could be considered free of common method bias [43]. Thus, the CMB in the present study was not a significant limitation. Another limitation of the study was that additional variables were not considered because this study focused on the algorithm and workers' responses. Future studies may explore additional predictors to expand the scope and explanatory power of the research model. Despite these limitations, the study has meaningful implications for research and practice.

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Appendix A

Table A1. Measurement Items.

Constructs	Items	Items	Sources
Algorithm Control	AC1	I perceive I am under constant surveillance and control by the algorithms.	[2,24]
	AC2	I feel under pressure to accept the jobs that are actively suggested by algorithms.	
	AC3	I am concerned about getting canceled and blocked if instructions by algorithms are not followed.	
Embracing	EB1	I enjoy my job as I see it as an easy opportunity to earn money.	[2,31]
	EB2	I have worked for this platform for many years, showing loyalty to the platform.	
	EB3	I recommend this platform to others to encourage them to join the platform.	

Table A1. *Cont.*

Constructs	Items	Items	Sources
Repeatability	RP1	I get access to repeated jobs during the work shift, including on the way home.	[2]
	RP2	I sometimes gain benefits from the platform's algorithms to generate extra earnings.	
	RP3	I feel assured about repeated income opportunities provided by algorithms.	
Switching	SWT1	I sign up to work on multiple ride-sharing platforms at the same time.	[2,31]
	SWT2	I monitor incoming ride requests on multiple platforms and choose the best ones.	
	SWT3	I take advantage of competing platforms to increase my earning potential.	
Uncertainty	UC1	I do not know whether a ride request by a platform consumer will be canceled.	[2]
	UC2	I have difficulties in calculating and predicting the exact amount of earnings.	
	UC3	I do not understand how the algorithm decides on job allocation and earnings.	

Appendix B

Table A2. Item-Factor Loadings and Cross-Loadings.

Constructs	Items	AC	EB	RP	SW	UT
Algorithm Control	AC1	**0.855**	−0.163	−0.153	0.148	0.457
	AC2	**0.887**	−0.247	−0.201	0.072	0.511
	AC3	**0.815**	−0.168	−0.097	0.062	0.493
Embracing	EB1	−0.139	**0.840**	0.534	0.208	−0.297
	EB2	−0.211	**0.839**	0.478	0.161	−0.272
	EB3	−0.215	**0.792**	0.554	0.321	−0.240
Repeatability	RP1	−0.153	0.434	**0.746**	0.177	−0.123
	RP2	−0.130	0.504	**0.843**	0.317	−0.265
	RP3	−0.156	0.600	**0.847**	0.198	−0.278
Switching	SWT1	0.109	0.213	0.213	**0.823**	−0.060
	SWT2	0.000	0.266	0.258	**0.815**	−0.047
	SWT3	0.148	0.230	0.242	**0.849**	0.026
Uncertainty	UC1	0.429	−0.254	−0.223	0.029	**0.795**
	UC2	0.334	−0.211	−0.128	−0.032	**0.710**
	UC3	0.560	−0.302	−0.289	−0.059	**0.868**

Appendix C

Table A3. Squared Pairwise Correlations and Assessment of the Discriminant Validity.

Construct	AC	EB	RT	SW	UT
Algorithm Control (AC)	**0.853**				
Embracing (EB)	−0.228	**0.824**			
Repeatability (RT)	−0.179	0.637	**0.813**		
Switching (SW)	0.109	0.283	0.285	**0.829**	
Uncertainty (UT)	0.571	−0.327	−0.281	−0.029	**0.793**

Legends: AC = Algorithm control, EM = Embracing, RT = Repeatability, SW = Switching, and UT = Uncertainty.

Appendix D

Table A4. Heterotrait–Monotrait Ratio (HTMT).

Construct	AC	EB	RT	SW	UT
Algorithm Control (AC)					
Embracing (EB)	0.288				
Repeatability (RT)	0.228	0.833			
Switching (SW)	0.155	0.365	0.374		
Uncertainty (UT)	0.730	0.437	0.358	0.080	

Legends: AC = Algorithm control, EM = Embracing, RT = Repeatability, SW = Switching, and UT = Uncertainty.

Appendix E

Table A5. Collinearity Statistics (VIF).

Construct	AC	EB	RT	SW	UT
Algorithm Control (AC)		1.486	1	1.486	1
Embracing (EB)					
Repeatability (RT)		1.086		1.086	
Switching (SW)					
Uncertainty (UT)		1.562		1.562	

Legends: AC = Algorithm control, EM = Embracing, RT = Repeatability, SW = Switching, and UT = Uncertainty.

References

1. Kellogg, K.C.; Valentine, M.A.; Christin, A. Algorithms at work: The new contested terrain of control. *Acad. Manag. Ann.* **2020**, *14*, 366–410. [CrossRef]
2. Möhlmannn, M.; Zalmanson, L.; Henfridsson, O.; Gregory, R.W. Algorithmic Management of Work on Online Labor Platforms: When Matching Meets Control. *MIS Q.* **2021**, *45*, 1999–2022. [CrossRef]
3. Gal, U.; Jensen, T.B.; Stein, M. Breaking the vicious cycle of algorithmic management: A virtue ethics approach to people analytics. *Inf. Organ.* **2020**, *30*, 100301. [CrossRef]
4. Wiener, M.; Cram, W.; Benlian, A. Algorithmic control and gig workers: A legitimacy perspective of Uber drivers. *Eur. J. Inf. Syst.* **2021**, 1–23. [CrossRef]
5. Rosenblat, A.; Stark, L. Algorithmic labor and information asymmetries: A case study of Uber's drivers. *Int. J. Commun.* **2016**, *10*, 3758–3785.
6. Tilson, D.; Lyytinen, K. Digitally induced industry paradoxes: Disruptive innovations of taxiwork and music streaming beyond organizational boundaries. In *Interdisciplinary Dialogues on Organizational Paradox: Learning from Belief and Science, Part A*; Emerald Publishing Limited: Bingley, UK, 2021; Volume 73, pp. 171–192.
7. Benbya, H.; Pachidi, S.; Jarvenpaa, S. Special issue editorial: Artificial intelligence in organizations: Implications for information systems research. *J. Assoc. Inf. Syst.* **2021**, *22*, 10. [CrossRef]
8. Burrell, J. How the machine 'thinks': Understanding opacity in machine learning algorithms. *Big Data Soc.* **2016**, *3*, 2053951715622512. [CrossRef]

9. Marabelli, M.; Newell, S.; Handunge, V. The lifecycle of algorithmic decision-making systems: Organizational choices and ethical challenges. *J. Strateg. Inf. Syst.* **2021**, *30*, 101683. [CrossRef]
10. Gautié, J.; Jaehrling, K.; Perez, C. Neo-Taylorism in the digital age: Workplace transformations in French and German retail warehouses. *Relat. Ind./Ind. Relat.* **2021**, *75*, 774–795.
11. Wang, B.; Schlagwein, D.; Cecez-Kecmanovic, D.; Cahalane, M.C. Beyond the factory paradigm: Digital nomadism and the digital future(s) of knowledge work post-COVID-19. *J. Assoc. Inf. Syst.* **2020**, *21*, 1379–1401. [CrossRef]
12. Liu, H.Y. Digital Taylorism in China's e-commerce industry: A case study of internet professionals. *Econ. Ind. Democr.* **2022**, 0143831X211068887. [CrossRef]
13. Spencer, D. Work in and beyond the Second Machine Age: The politics of production and digital technologies. *Work Employ. Soc.* **2017**, *31*, 142–152. [CrossRef]
14. Addo, A. Orchestrating a digital platform ecosystem to address societal challenges: A robust action perspective. *J. Inf. Technol.* **2022**, *37*, 359–386. [CrossRef]
15. Head, S. *Mindless: Why Smarter Machines Are Making Dumber Humans*; Basic Books: New York, NY, USA, 2014.
16. Graham, M.; Hjorth, I.; Lehdonvirta, V. Digital labour and development: Impacts of global digital labour platforms and the gig economy on worker livelihoods. *Transf. Eur. Rev. Labour Res.* **2017**, *23*, 135–162. [CrossRef]
17. Chan, N.K. Algorithmic precarity and metric power: Managing the affectve measures and customers in the gig economy. *Big Data Soc.* **2022**, *9*, 20539517221133779. [CrossRef]
18. Jeske, D. Remote workers' experiences with electronic monitoring during Covid-19: Implications and recommendations. *Int. J. Workplace Health Manag.* **2022**, *15*, 393–409. [CrossRef]
19. Möhlmannn, M.; Alves de Lima Salge, C.; Marabelli, M. Algorithm sensemaking: How platform workers make sense of algorithmic management. *J. Assoc. Inf. Syst.* **2023**, *24*, 35–64. [CrossRef]
20. Veen, A.; Barratt, T.; Goods, C. Platform-capital's 'app-etite'for control: A labour process analysis of food-delivery work in Australia. *Work Employ. Soc.* **2020**, *34*, 388–406. [CrossRef]
21. Wood, A.J.; Graham, M.; Lehdonvirta, V.; Hjorth, I. Good gig, bad gig: Autonomy and algorithmic control in the global gig economy. *Work Employ. Soc.* **2019**, *33*, 56–75. [CrossRef]
22. Lee, M.K.; Kusbit, D.; Metsky, E.; Dabbish, L. Working with machines: The impact of algorithmic and data-driven management on human workers. In Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems, Seoul, Republic of Korea, 18–23 April 2015; pp. 1603–1612.
23. Kuhn, K.M.; Maleki, A. Micro-entrepreneurs, dependent contractors, and instaserfs: Understanding online labor platform workforces. *Acad. Manag. Perspect.* **2017**, *31*, 183–200. [CrossRef]
24. Newlands, G. Algorithmic surveillance in the gig economy: The organization of work through Lefebvrian conceived space. *Organ. Stud.* **2021**, *42*, 719–737. [CrossRef]
25. Pachidi, S.; Berends, H.; Faraj, S.; Huysman, M. Make way for the algorithms: Symbolic actions and change in a regime of knowing. *Organ. Sci.* **2021**, *32*, 18–41. [CrossRef]
26. Schuetz, S.; Venkatesh, V. The rise of human machines: How cognitive computing systems challenge assumptions of user-system interaction. *J. Assoc. Inf. Syst.* **2020**, *21*, 460–482. [CrossRef]
27. Robert, L.P.; Pierce, C.; Marquis, L.; Kim, S.; Alahmad, R. Designing fair AI for managing employees in organizations: A review, critique, and design agenda. *Hum. Comput. Interact.* **2020**, *35*, 545–575. [CrossRef]
28. Bucher, E.L.; Schou, P.K.; Waldkirch, M. Pacifying the algorithm–Anticipatory compliance in the face of algorithmic management in the gig economy. *Organization* **2021**, *28*, 44–67. [CrossRef]
29. Cameron, L.D.; Rahman, H. Expanding the locus of resistance: Understanding the co-constitution of control and resistance in the gig economy. *Organ. Sci.* **2022**, *33*, 38–58. [CrossRef]
30. Curchod, C.; Patriotta, G.; Cohen, L.; Neysen, N. Working for an Algorithm: Power Asymmetries and Agency in Online Work Settings. *Adm. Sci. Q.* **2020**, *65*, 644–676. [CrossRef]
31. Karanović, J.; Berends, H.; Engel, Y. Regulated dependence: Platform workers' responses to new forms of organizing. *J. Manag. Stud.* **2021**, *58*, 1070–1106. [CrossRef]
32. Gregory, R.W.; Henfridsson, O.; Kaganer, E.; Kyriakou, H. The role of artificial intelligence and data network effects for creating user value. *Acad. Manag. Rev.* **2021**, *46*, 534–551. [CrossRef]
33. Muller, Z. Algorithmic Harms to Workers in the Platform Economy: The Case of Uber. *Columbia J. Law Soc. Probl.* **2020**, *53*, 167–210.
34. Griesbach, K.; Reich, A.; Elliott-Negri, L.; Milkman, R. Algorithmic control in platform food delivery work. *Socius* **2019**, *5*, 2378023119870041. [CrossRef]
35. Keil, M.; Tan, B.C.; Wei, K.; Saarinen, T.; Tuunainen, V.; Wassenaar, A. A Cross-Cultural Study on Escalation of Commitment Behavior in Software Projects. *MIS Q.* **2000**, *24*, 299–325. [CrossRef]
36. Goodhue, D.L.; Lewis, W.; Thompson, R. Does PLS have advantages for small sample size or non-normal data? *MIS Q.* **2012**, *36*, 981–1001. [CrossRef]
37. Chin, W.W.; Marcolin, B.L.; Newsted, P.R. A partial least squares latent variable modeling approach for measuring interaction effects: Results from a Monte Carlo simulation study and an electronic-mail emotion/adoption study. *Inf. Syst. Res.* **2003**, *14*, 189–217. [CrossRef]

38. Hair, J.; Hollingsworth, C.L.; Randolph, A.B.; Chong, A.Y.L. An updated and expanded assessment of PLS-SEM in information systems research. *Ind. Manag. Data Syst.* **2017**, *117*, 442–458. [CrossRef]
39. Hair, J.; Anderson, R.; Tatham, R.; Black, W. *Multivariate Data Analysis*, 5th ed.; Prentice-Hall: Englewood Cliffs, NJ, USA, 1998.
40. Fornell, C.; Larcker, D.F. Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *J Mark. Res.* **1981**, *18*, 39–50. [CrossRef]
41. Henseler, J.; Ringle, C.M.; Sarstedt, M. A new criterion for assessing discriminant validity in variance-based structural equation modeling. *J. Acad. Mark. Sci.* **2015**, *43*, 115–135. [CrossRef]
42. Bucher, E.; Schou, P.K.; Frischherz, F. The emergence of self-disciplinary practices in the face of algorithmic governance. In *Academy of Management Proceedings*; Academy of Management: Briarcliff Manor, NY, USA, 2019; p. 13825.
43. Kock, N. Common method bias in PLS-SEM: A full collinearity assessment approach. *Int. J. e-Collab.* **2015**, *11*, 1–10. [CrossRef]